MODELING URBAN WARFARE: JOINT SEMI-AUTOMATED FORCES IN URBAN RESOLVE

THESIS

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Abstract

The United States military is performing operations in urban environments with increasing frequency. Current Department of Defense doctrine is poorly suited to train and equip today's warriors with the tools and experience necessary to fight and win in modern sprawling cities. In order to "close the gap," the U.S. Joint Forces Command's Joint Experimentation Directorate led an effort to run a massively distributed simulation of a synthetic urban environment utilizing human-in-the-loop operators called URBAN RESOLVE. The synthetic environment simulated the city of Jakarta with over 1,000,000 buildings and structures and over 120,000 civilian entities. A Red force retreated into the city while a Blue force attempted to determine the enemy's Order of Battle. The exercise generated over 3.7 terabytes of data in seven distinct trials. This research evaluated the time required to identify targets after detection and the accumulation of identifications over time, and searched for trends between the seven design trials and between target groups. Two trends emerged from this research. First, there was a notable difference in the time required to identify a target once it has been detected based on its target group. Second, two design trials that are expected to demonstrate show counter-intuitive results.

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I would like to express my sincere appreciation to my faculty advisor, Dr. John O. Miller, for his guidance and support throughout the course of this thesis effort. I sincerely appreciated your insight and experience. To Dr Philip Amburn, thank you for your boundless enthusiasm and willingness to help as I tried to find my way. To Ms Susan Donoff, I cannot thank you enough for your countless hours spent trying to convert my data into a useable format. I would like to thank Mr. Greg Rafuse and Mr. Drew Schenkelberg for spending hours on the phone and email answering some very open ended questions.

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Alex B. Anastasiou

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MODELING URBAN WARFARE: JOINT SEMI-AUTOMATED FORCES IN URBAN RESOLVE

I. Introduction

Background

In the history of warfare, one of the enduring truths has always been, attack cities as a last resort. In The Art of War Sun Tzu wrote, “The worst policy is to attack cities. Attack cities only when there is no alternative…” (Tzu, 1971:78-79). Among other difficulties and complications, Sun Tzu recognized the extreme difficulty of attacking walled cities. Successfully laying siege to such a city, while possible, required expending vast amounts of materiel and human resources. There are few walled cities left in the world today, and the lethality of modern weapons eliminates their utility as an effective defense against attack. Nevertheless, modern urban combat presents its own host of difficulties. Wholesale bombing of cities and the ensuing civilian casualties is both unnecessary and politically unacceptable. What is more is the realization that it is no longer enough for the United States to defeat its enemies; we must make all efforts to provide stability and establish a culture of democracy. The result is that the United States finds itself not only in the unenviable position of engaging in open urban combat operations, but also performing peace keeping and stability operations against an insurgency bent on hastening our departure.

The challenge facing the Department of Defense (DoD) is developing the tactics, training, and equipment that will prepare our forces to fight in such urban scenarios. Before the end of the cold war, the DoD's primary focus was to prepare for a massive force on force battle against the USSR. Although urban combat was sure to take place as the battle raged across the European continent, little attention was given to the needs of effective urban combat. What little attention there was, focused primarily on small villages and full force combat not peace keeping and stability operations in a sprawling metropolis with millions of people, and millions of buildings and structures (Fontenot, 2003). However, recent advances in computer technology, experimental architecture design, networking, and a renewed focus in light of events in the Middle East, has resulted in the genesis of large scale distributed synthetic environments designed to provide the command and control warrior the ability to practice operations in a modern urban landscape.

URBAN RESOLVE is a three-phase exercise sponsored by U.S. Joint Forces Command's (JFCOM) Joint Experimentation directorate (J9). The goal of URBAN RESOLVE is to "… guide the development of critical warfighting capabilities for the future joint force commander, with a particular focus on those needed for effective urban operations," (Urban, 2006). At its essence, URBAN RESOLVE provides a mechanism to evaluate the utility of near-future intelligence, surveillance, and reconnaissance (ISR) assets within the urban environment and to develop tactics, techniques, and procedures (TTP) to aid the joint forces commander in gaining situational awareness of enemy activities.

URBAN RESOLVE utilizes the Joint Semi-Automated Forces synthetic environment to allow real-time human-in-the-loop (HITL) interaction by both a Blue and Red force within a synthetic version of the Indonesian capital of Jakarta complete with over 1,000,000 buildings and over 120,000 non-combatants moving about the city in a culturally accurate manner (Wielhouwer, 2005:12-13 and Rafuse, 2006). URBAN RESOLVE participants control a constellation of approximately 250 ISR assets that generate tracks from approximately 1100 enemy targets attempting to hide within the city's civilian population.

A critical aspect of such a large simulation is the massive data collection and data analysis needs. A single twenty-four hour run of URBAN RESOLVE generated approximately 100 gigabytes of data and over forty million rows of data. The entire first phase, which consisted of seven experimental designs, generated over 3.5 terabytes of storage space. Yet despite all this data there was only a single replication for each experimental design. The lack of replications presents difficulties when performing statistical analysis due to the inability to make assumptions about the data such as normality and independence.

Problem Statement

This thesis analyzes data produced from the exercise URBAN RESOLVE Phase I by manipulating the data into various formats and using nonparametric statistics in order to find trends in the data that will provide additional insight into the results of the exercise. The challenge for this research effort is to analyze a dataset containing over 40 million rows of data totaling 3.7 terabytes in size. In addition, there are only single replications for each of the seven experimental design trials. Finally, the experimental design varied multiple design parameters between trials and made it difficult to determine the exact cause of changes observed from trial to trial.

Scope

This research effort will focus on the track-data collected during URBAN RESOLVE Phase I. The data consists of the complete listing of all tracks generated when a Blue force sensor detects a target within the simulation. The data includes target type, detecting sensor, and detection time. If identification was made, the data also includes the identifying sensor and time of identification. Analysis will focus specifically on the time required to identify a target (TTI), after a detection has occurred, and how that time varies between design trials, target groups (soldiers, civilians, mechanized, etc), and the detecting platform. This research will also investigate the rate at which identifications are generated for each trial and target group. The intent is to search for trends in the data that have not been previously identified, and which may indicate areas for further study.

Outline

The literature review chapter provides an overview of modeling and simulation in the Department of Defense (DoD), a look at combat modeling past and present, the growing importance of urban combat, virtual simulation, synthetic environments, and finally URBAN RESOLVE. The methodology chapter will discuss the URBAN RESOLVE experimental architecture, experiment design, data collection and reduction, and finally data analysis. Chapter IV will present the results of our data analysis and

Chapter V will provide a synopsis of the analysis, obstacles encountered, the significance of the research and finally recommendations for future research.

II. Literature Review

Chapter Overview

The purpose of this chapter is to provide an overview of the various aspects of combat modeling in a real-time high-resolution synthetic environment. Particular attention will be paid to combat modeling's ability to aid in understanding the complex urban battlefield. This chapter begins with a general discussion of modeling and simulation and their applications within the DoD. This is followed by an overview of attrition based combat modeling and its limits. Next will be a discussion of the increased role of urban combat and asymmetrical conflicts faced by the U.S. military. Following this is a discussion of synthetic environments and the challenges faced in creating applicable synthetic urban environments and modeling asymmetrical threat behavior. Finally, this chapter will discuss the Joint Forces Command sponsored exercise URBAN RESOLVE.

Modeling and Simulation

According to the Defense Modeling and Simulation Office (DMSO), modeling and simulation in the DoD is broken into three functional areas: training, analysis, and acquisition. Models can be further categorized based on their resolution and level of aggregation. DoD5000.59-M, Department of Defense Modeling and Simulation (M & S) Glossary (1998), defines resolution and aggregation as, "The degree of detail and precision used in the representation of real world aspects in a model or simulation," and "The ability to group entities while preserving the effects of entity behavior and interaction while grouped," respectively. The DoD Services each have extensive libraries of models and simulations they use to satisfy these various functional areas. These models span the spectrum from modeling airfoil fluid dynamics, to operational planning of a major theater war. Functionally, they range from training operators in weapon system simulators, analyzing the effects of integrating a new weapon system into the inventory, and supporting the effectiveness and suitability determination of an acquisition program. The DMSO Modeling and Simulation Resource Repository (MSRR) contains hundreds of government accepted models and simulations that may be used for analysis within the DoD. The hierarchy and functional areas of models and simulations used by the DoD are represented in Figure 1.

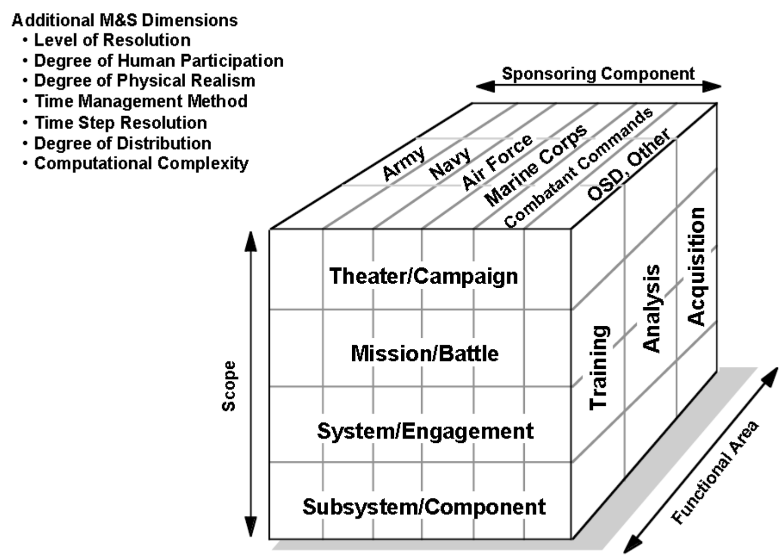

Figure 1. Hierarchy and Functional Areas of DoD Combat Models (DoD 5000.59-P, 1995)

Combat Modeling

Combat modeling has historically focused on modeling the attrition of forces in open combat. Effectively modeling a complex event such as combat typically requires some minimal level of aggregation. Even with the aid of computers, aggregation is often required for a timely answer due to limits of processing speed and storage requirements. The work of Frederick W. Lanchester has dominated combat modeling attrition analysis since World War I. In 1914, Lanchester described warfare using two basic models. The first, based on "ancient" warfare, assumes a battle to be a collection of one-on-one duels and results in a casualty exchange ratio proportional to force size. The second model, based on "modern" warfare, attempts to capture the effects of weapon lethality and the ability to concentrate fire, which can result in a many-on-one scenario. Here the casualty exchange ratio is inversely proportional to the size of the enemy force. These two models are termed the Linear and Square laws respectively (Hartman, 1997:6-2)

The Lanchester attrition models aggregate warfare. In doing so, they treat all combatants identically, and ignore differences in individual combatants such as skill, state of alertness, equipment state of repair, lethality, logistics, complex terrain, intelligence etc. Over the years, manipulations of the basic equations have allowed for heterogeneous applications of the Lanchester models that attempt to mitigate some of the above limitations. However, none of the various additions or complications are able to capture the impact of maneuver warfare, information, command and control (C^2), civilian casualty avoidance, and asymmetric warfare. When modeling at the theater level of war in a force-on-force scenario, these facts may be of little consequence. However, modern warfare is increasingly dependant on C^2, intelligence, and maneuver.

Urban Combat

The battlefield of modern warfare is changing as well. In the post-cold war era, the United States has demonstrated its ability to prosecute a conventional force-on-force battle with relative ease. Unfortunately, our adversaries have noticed this too and avoid open combat whenever possible. In addition, US deployments abroad have grown in number as the world has become more urbanized and the US finds itself performing combat operations in the urban environment with increasing regularity (Wielhouwer, 2005:2-5). In the US Army's analysis of Operation Iraqi Freedom, *On Point* (2003), the authors discuss the fact that the 1991 Gulf War showed the Iraqi military the futility of facing coalition forces in open desert combat. Their reaction to this stark reality became apparent in 2003 as they massed their forces in urban areas such as Baghdad. Although victory was swift, the on going insurgency shows that the urban environment is where the US is likely to face its greatest future challenge. Finally, US military operations will continue to include military operations other than war (MOOTW) in the urban environment with ever-increasing frequency (Wielhouwer, 2005:2).

An important acknowledgment made in *On Point* (2003), is the DoD's critical weakness at developing effective joint doctrine, tactics, and training for the modern urban environment. Until recently, urban combat training facilities were limited to simulating small towns and villages, rather than the vast urban metropolises common today. Furthermore, DoD modeling and simulation capabilities have lacked the detail, scale, and real-time capacity required to realistically train in a virtual simulated urban environment.

Virtual and Constructive Simulation

The DoD must therefore construct robust simulated environments that will allow military planners to effectively develop and test doctrine for joint urban operations (JUO). Virtual and constructive simulations are defined, respectively, by DMSO as "… real people operating simulated systems," and "… simulated people operating simulated systems." A third type of simulation, live simulation, involves "real people operating real systems." (DoD 5000.59-P, A-6:1998) Unfortunately, operating military hardware within a real urban environment is problematic at best. Nor are we likely to build a full-scale model of a modern urban area complete with non-combatants going about their daily, simulated, lives. We are therefore limited to training within a virtual and constructive world where key players can develop and practice tactics, techniques, and procedures (TTP) in a realistic simulated urban environment.

A synthetic urban environment must include, at a minimum: a robust building set and terrain map, non-combatants acting in a culturally accurate manner, intelligent adversaries, vehicle traffic, and intelligence, surveillance, and reconnaissance (ISR) assets (Dehncke, 2005). These features, and more, must be implemented so that they operate in real-time and allow for human-in-the-loop (HITL) interaction.

Creating a complex urban environment is not a simple task. Only a few terrain maps exist with high levels of detail and even fewer building data sets exist that realistically reproduce the millions of structures that may be present in a modern urban area. Nor does merely representing buildings as solid objects suffice. A key feature of the urban environment is the complexity created by the presence of structures that provide concealment and firing positions. Structurally they must possess, multiple levels, allow for realistic structural damaged, fortification, etc. Thus, it is desirable to represent a building as a fully interactive three-dimensional structure with openings that allow entry and exit of entities and projectiles, occupation of and travel between multiple levels, and realistic damage based on weapons effects (Miller, 2003).

In addition to the buildings and terrain, a JUO training environment must include realistic simulation of non-combatant entities. The requirement to minimize civilian casualties and the need to identify combatants concealing themselves within the population demands an accurate depiction of non-combatants. These entities must behave in a culturally consistent manner performing daily activities on a realistic timetable (Dehncke, 2005). However, modeling crowds of people goes beyond accurately simulating a single individual's behavior under a given situation. Accurately modeling a crowd requires allowances for different entities to have different motivations and behaviors when faced with the same situation. A model that includes identically behaving entities will not appear realistic even if a single entity behaved in a realistic manner (Ulicny, 2001).

Further complicating the problem for military simulation is the need to model enemy forces in the urban environment. No longer is it a simple matter to simulate the behavior of an enemy combatant engaging in open combat using conventional warfare tactics. Although urban operations can take the form of open combat with a clear enemy, the more difficult task of defending against an insurgency or performing peacekeeping operations is becoming more prevalent as was demonstrated during operations in Kosovo, Mogadishu, and now Iraqi. The challenge in such environments is to model the insurgents as they attempt to blend in while performing clandestine nefarious activities.

Synthetic Environment and Semi-Automated Forces

In the past, senior leaders were content to practice the art of war by participating in what could best be described as glorified games of Risk, controlling the movements of divisions, corps, and even entire armies as the battle progresses. The need for senior leaders to train in large-scale, yet highly detailed, battle spaces has become a critical issue. Senior leaders and strategists must have the ability to train for the more complex and intricate environments facing them today and in the future. The explosion of ISR assets and the transformation to network centric warfare has provided unique opportunities but also unique challenges. The ability to obtain vast quantities of data is an incredible achievement, however, data is not information, and information is not understanding.

The ability to generate large-scale high-resolution synthetic environments is relatively new. Although combat modeling state-of-the-art has been marching at a steady pace towards such a goal, it is only recently that all the pieces required have fallen into place. Much of the credit can be assigned to the huge advances in computing power that have occurred in recent years. However, just as important as the advances in technology have been, so has the evolution of the need for such environments.

URBAN RESOLVE

In response to the DoD's need for realistic urban training and improved tactics and systems, the U.S. Joint Forces Command's (JFCOM) Joint Experimentation directorate (J9) sponsored the experiment URBAN RESOLVE in 2004. URBAN RESOLVE is a three-phase effort, extending to 2007 and beyond, with the goal to, "… guide the development of critical warfighting capabilities for the future joint force commander, with a particular focus on those needed for effective urban operations," (Urban, 2006). The URBAN RESOLVE experiment takes place within a massive synthetic urban environment that consists of 1.8+ million building structures. Of those structures, 65,000 of them allow for increased interaction such that entities can enter the buildings, fight inside, and see the street from within the building. A key aspect of the synthetic environment in URBAN RESOLVE is the simulation of a dense urban population, called cultural features, that included over 124,000 entities with approximately 35,000 of them active and behaving in a culturally accurate manner. Testing has shown that over 1 million entities are possible. Green Force participants controlled the cultural-features (Wielhouwer, 2005:12-13 and Rafuse, 2006).

The first phase of URBAN RESOLVE, URBAN RESOLVE 2015, occurred between June and October 2004. URBAN RESOLVE 2015's goal was to assess the ability of the Joint Forces Commander to attain situational awareness utilizing a myriad of current and future ISR assets. The Blue Forces' mission was to employ ISR assets to detect and predict the movements and presence of Red Force entities as they moved about within the dense cultural features of the synthetic environment, and to stealthily deploy and conceal their ISR assets. Meanwhile the Red Forces' mission was to challenge, adapt, and react to the Blue Force in a manner consistent with an aggressive and adaptive enemy (Wielhouwer, 2005:10-11). The results from Phase 1 were impressive. The Blue Force detected 80% of the Red Forces, identified 50%-60% of the Red Forces' current activities, and anticipated 60%-70% of their future actions (Wielhouwer, 2005:14).

The backbone technologies that made URBAN RESOLVE possible were the JSAF synthetic environment, the use of distributed Scalable Parallel Processors (SPP) clusters, the Defense Research Engineering Network (DREN), and the Command and Control (C2) workstations used for HITL warfighter involvement (Dehncke, 2005). The JSAF environment was responsible for providing the synthetic environment in which the exercise occurred as well as the entity level Blue and Red Forces, and the Green team's cultural features. Modeling of the sensor data was performed by the Simulation of Location and Attack of Mobile Enemy Missiles (SLAMEM) federate. Modeling of HUMINT data was provided by the SOAR-SOF federate. The SPP clusters provided the raw processing power required for JSAF to generate the environment and entities. The SPP clusters are located at the Maui High Performance Computer Center (MHPCC) in Maui, HI and the Aeronautical Systems Center Major Shared Resource Center (ASC-MSRC) at Wright Patterson Air Force Base, OH. Additional computing resources for Blue, Red, and Green Force operations, simulation control, and the analysis team were located at Ft Belvoir, VA, San Diego CA, and Suffolk, VA. Linking all these distant resources together in real-time was the DREN as depicted in Figure 2 (Dehncke, 2005).

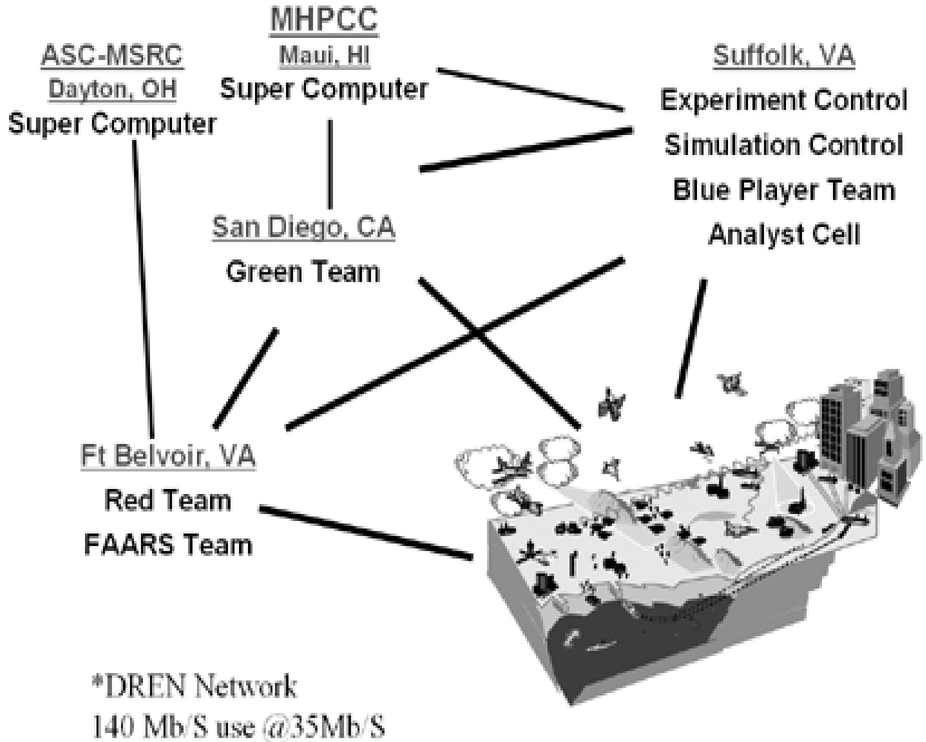

Figure 2. Connectivity between distributed participants (Dehncke, 2005)

The C2 systems for warfighter interaction consist of a JSAF display responsible for providing the shared tactical picture as perceived by the participants, a JSAF control terminal for sensor controls, data display assessment, track management, and a terminal for collaborative tools such a text, chat, voice and graphics (Figure 3).

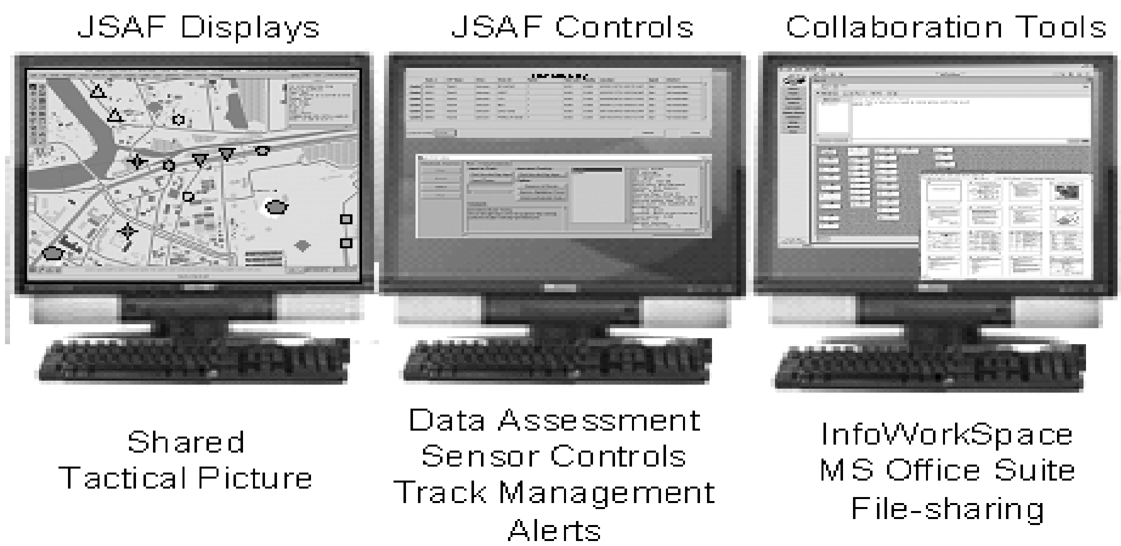

Figure 3. Operator's C2 Workstation (Dehncke, 2005)

The process of generating a track in URBAN RESOLVE involves the generation and transmission of "ground truth" data for all entities (Blue, Red, and Green Forces). As these entities move around the synthetic environment, they may enter the sensor footprint of an ISR entity. At this point, the simulation decides if the entity is visible to the sensor based on various criteria such as line-of-site (LOS). If the entity is detectable by the sensor, this triggers an "interaction" event. The interaction event is then sent to a confusion matrix, in the SLAMEM federation, that adds a level of uncertainty to the interaction. The confusion matrix uses data related to the sensors capabilities against the given target entity, environmental conditions, etc. and generates a track indicating the possible identity of the track and a confidence value. The tracks are then displayed for the warfighters on their consoles. As multiple sensor hits accumulate for a given track, a process within SLAMEM automatically correlates tracks to increase the confidence level of the track's label. An example would be three tracks generated by three different sensors on a given moving target. When considered separately, each of those tracks may have a low confidence that the target in question is a tank. However when considered together, those three tracks may indicate, with a high level of confidence, that the track in question is a T-72 tank (Rafuse, 2006).

As the warfighters observe the multitude of tracks on their consoles, they can make inferences as to the intent of the track(s). These inferences are called situational awareness objects (SAO) that can be considered notional "buckets" that contain a track, or tracks. An SAO indicates the operator's guess as to the track's intent and provides a mechanism for the operator to share this information with other players. For example, a series of tracks labeled as vehicles, containing armed civilians, known insurgent leaders, and traveling together along the same route, may be labeled as an enemy convoy and placed in an SAO. Analysis of these SAOs is what allowed the exercise evaluators to determine if the Blue Force was able to accurately determine and predict the activities of the Red Force (Rafuse, 2006).

What should become apparent from the discussion thus far are the vast quantities of data such an exercise generates. The dataset for a single twenty-four hour simulation trial, excluding all cultural-feature data, was approximately ninety to one hundred twenty gigabytes containing forty to fifty million rows of data. The entire URBAN RESOLVE 2015 Phase 1 exercise consisted of seven such trials. The complete dataset, including all cultural-features, consumed over 3.5 terabytes of disk space. This presents a significant obstacle for data analysis and presents opportunities for new techniques in analysis and data mining.

Collecting such a vast amount of data presented certain obstacles as well. Early data collection schemas attempted to push all logged data to a central repository. However, as the exercise environment grew, the data transfer requirement overloaded the physical network and resulted in data loss. In addition, it was not possible to log some simulation event data because of the way cluster computers operate. To address these limitations URBAN RESOLVE Phase I utilized interceptor/logger applications operating at each computing cluster. An aggregator application was used to request data of interest from the individual computing clusters (Graebener, 2004:2-3). The result was a data collection schema that allowed robust collection without saturating the network and afforded the analysts near-real-time access to, and analysis of, the data. The backbone of the database was the open source database engine MySQL. The open source nature of MySQL allowed the analysts to modify the actual application to suit their needs.

The initial intent of URBAN RESOLVE was as a tool to evaluate the ability of current and future ISR assets to aid the warfighter in gaining situational awareness in a modern urban setting. The success of Phase 1 showed senior leaders the potential of applying URBAN RESOLVE's experimental approach to problems faced in present day urban operations. The result was an expansion of URBAN RESOLVE to establish a baseline of current urban warfare capabilities, and address current challenges faced by our forces. The two new directives included adapting the modeling and simulation framework to support its use as a mission planning and rehearsal tool for deploying forces, and supporting development of more effective responses to non-traditional mortar attacks in Iraq (Wielhouwer, 2005:11-12).

Summary

This literature review investigated the current scope of modeling and simulation in the DOD and the history of combat modeling. The review then continued with a discussion of urban combat and the DoD's need to better train and equip our forces to operate in the urban environment. This led to an examination of computer generated synthetic environments, semi-automated forces, and ultimately the URBAN RESOLVE exercise. Finally, this literature review showed that data collection, reduction and analysis is a significant challenge to such a large-scale event.

III. Methodology

Chapter Overview

This purpose of this chapter is to provide an overview of the methodology employed for the URBAN RESOLVE exercise and the methods used in this research effort to analyze the data generated from the exercise. It begins with a discussion of URBAN RESOLVE's experimental architecture, experimental design, data collection methods, and data analysis. This chapter concludes with a discussion of the limitations of the available data, a nonparametric method for generating confidence intervals for the median of single-population data, and finally a description of the analysis performed.

Experiment Architecture

As previously discussed, URBAN RESOLVE Phase I was an exercise intended to investigate the utility of new and emerging ISR technologies, and the TTPs used to employ them, in a large-scale HITL synthetic urban environment. The URBAN RESOLVE exercise took place in the simulated Indonesian capital city of Jakarta. The Red Forces withdrew into the city to mount a final defense and possess medium-range ballistic missiles (MRBM). The Blue Force Joint Intelligence and Fusion Cell (Blue Cell) controlled an array of sensor platforms that included unmanned aerial vehicles (UAV), organic aerial vehicles (OAV), and unmanned ground sensors (UGS). The Blue Cell controlled these platforms to gain situational awareness of the enemy's activities. The UAVs operated at medium/high altitude, provided a "persistent" stare into the area of interest (AOI), and were responsible for initiating and maintaining tracks of Red entities. The OAVs operated a low altitude were ale to flow down into the AOI and provided a closer look to locate, track, and identify Red entities. The OAVs were also capable of placing radio frequency tags onto vehicles and personnel. The UGSs assisted the Blue cell in locating, tracking, and identifying Red entities, and in some cases tagging entities (Burke, 2005:9). A broad range of sensors were available, and included acoustic/seismic, magnetometer, Ku-band moving target indicator (MTI), Ku-band synthetic aperture radar (SAR), foliage penetrating SAR, LADAR, Laser Profilers, Electro-optical/Infra-red (EO/IR), and X-ray sensors. In addition, special operations forces (SOF) and HUMINT were available (Burke, 2005:24-30). Tracks within URBAN RESOLVE were generated using the following process:

- A sensor foot print was projected onto the AOI
- If an entity fell within that foot print it was tested for LOS, velocity, and concealment
- If the entity was deemed "visible" to the sensor the following occurred:
    - A random draw was made and compared against the probability of detection for the sensor-target pairing to determine if the sensor actually detects a target
    - If a detection occurred the entity was processed through a confusion matrix to determine how the target is classified
    - The track was then either passed to the Blue Cell, updated if the track already existed, or used to cue another sensor-platform pair

Target correlation was modeled perfectly such that two or more sensors that detected the same target resulted in a single track. Similarly, two targets were never classified as the same target if they were in close proximity (Burke, 2005:31-32).

Experiment Design

URBAN RESOLVE Phase I exercise encompassed seven different scenarios. The exercise variables were Blue Force platforms inventory, target signature, Red Force activity level, and availability of Tags. The complete exercise design is shown in Table 1. The parameter "reduced Blue platform inventory" meant the removal of all UAVs with hyperspectral and EO/IR sensors from the simulation. The remaining platforms were the UAVs with SAR sensors. The intent of the reduction was to simulate a low cloud ceiling. The parameter for "Red Force signature reduction" simulated attempts by the Red Force to reduce or alter their signature return. The reduced signature effect was modeled in the simulation by modifying the detection and identification capabilities of Blue Force sensors relative to those targets. Red Force activity level (active/inactive) indicates the proportion of the force that began the event outside the AOI. An active Red Force started the event with 70% of its forces outside the AOI while an inactive force started with 70% of forces already inside the AOI. The presence of Tags in the exercise was varied by allowing or disallowing their use (Burke, 2005:ES7-ES9). Tags are small radio frequency ID (RFID) tags that are attached to enemy personnel and equipment by either OAVs or UGSs. Blue Force sensors can track the Tags and provide an effective method for maintaining situational awareness of a track's position and identity even if the track is lost for extended periods within the urban clutter.

An inspection of Table 1 reveals a flaw in the experimental design. In each trial, more than a single parameter is changed. Designing trials with a multiple parameter changes makes it difficult to correlate observed changes in the data to changes in a particular parameter. A compounding factor to the poor experimental design is the lack of multiple replicate runs for each trial. This is expected from an exercise of this type due to the large amount of time and resources required to perform a single replication. With only single replications, that are not independent, classical statistical comparative analysis is not possible.

Table 1. Exercise Design (Burke, 2005:16-17)

<table>
<tr><th colspan="2">Trial 1</th></tr>
<tr><td colspan="2">• Full blue platform inventory
• Full target signature
• Active Red
• 48-hour trial
• Tags</td></tr>
<tr><th>Trial 2A</th><th>Trial 2B</th></tr>
<tr><td>• Full Blue platform inventory
• Full targets signature
• Inactive Red
• Tags
• 24-hour trial</td><td>• Reduced Blue platform inventory
• Full target signature
• Inactive Red
• Tags
• 18-hour trial</td></tr>
<tr><th>Trial 3A</th><th>Trial 3B</th></tr>
<tr><td>• Full Blue platform inventory
• Reduced target signature
• Active Red
• Tags
• 24-hour trial</td><td>• Reduced Blue platform inventory
• Full target signature
• Active Red
• Tags
• 24-hour trial</td></tr>
<tr><th>Trial 4A</th><th>Trial 4B</th></tr>
<tr><td>• Full Blue platform inventory
• Full target signature
• Active Red
• No Tags
• 24-hour trial</td><td>• Reduced Blue platform inventory
• Reduced target signature
• Active Red
• No Tags
• 24-hour trial</td></tr>
</table>

Data Collection and Reduction

Data collection in URBAN RESOLVE was a monumental task. In any given event, the constellation of Blue Force platforms numbered between 115 and 330, many of which had multiple sensors. The constellation was reporting detections on over

1100 Red Force entities dispersed within a population of over 100,000 cultural features (Burke, 2005:77-80). Each event run generated approximately 40-50 million rows of data and consumed 90-120 gigabytes of physical storage space (Rafuse, 2006). Table 2 shows an example of one of the many tables available. This particular table shows the data generated from a single contact report when a sensor detects an entity.

Table 2. Raw MySQL data table from URBAN RESOLVE Phase I (2005)

Field	DataType	Description
uniqueIndex	STRING	Unique ID for record within individual logger database
node	STRING	Node hostname
spaceName	INTEGER	RTI Namespace Name
timestamp	FLOAT	Local machine timestamp for record (when written)
platform_id_ID	STRING	Identifies the platform this sensor is mounted on.
sensor_id	INTEGER	Sensor ID on this platform
sensor_plan_mode	INTEGER	Internal ID of sensor/mode/exploitation combination
batch_flag	INTEGER	Internal use (beg/middle/end of collections)
FOPEN_depth	FLOAT	Two-way detection threshold (meters)
owning_force	STRING	Force of entity object (Friendly/Opposing/Neutral)
platform_type_EntityKind	INTEGER	Enumeration value for entity object - Kind
platform_type_Domain	INTEGER	Enumeration value for entity object - Domain
platform_type_CountryCode	INTEGER	Enumeration value for entity object - Country
platform_type_Category	INTEGER	Enumeration value for entity object - Category
platform_type_Subcategory	INTEGER	Enumeration value for entity object - SubCategory
platform_type_Specific	INTEGER	Enumeration value for entity object - Specific
platform_type_Extra	INTEGER	Enumeration value for entity object - Extra
sensor_location_X	DOUBLE	GCS Location of entity object - X Value
sensor_location_Y	DOUBLE	GCS Location of entity object - Y Value
sensor_location_Z	DOUBLE	GCS Location of munition object - Z Value
platform_velocity_Xvelocity	FLOAT	Movement velocity of entity object - X Value
platform_velocity_Yvelocity	FLOAT	Movement velocity of entity object - Y Value
platform_velocity_Zvelocity	FLOAT	Movement velocity of entity object - Z Value
sensor_mode	STRING	Mode of operation for sensor (MTI, STRIP_EO, etc.)
comment	STRING	The comment to attach.
entity_id_ID	INTEGER	Ground truth id of the entity that got painted.
location_X	DOUBLE	Ground truth GCS Location of entity object - X Value
location_Y	DOUBLE	Ground truth GCS Location of entity object - Y Value
location_Z	DOUBLE	Ground truth GCS Location of entity object - Z Value
velocity_XVelocity	FLOAT	Movement velocity of entity object - X Value
velocity_YVelocity	FLOAT	Movement velocity of entity object - Y Value
velocity_ZVelocity	FLOAT	Movement velocity of entity object - Z Value
appearance	INTEGER	Appearance bits of the painted vehicle.
building_attributes	INTEGER	Attribute bits of the painted building.
detection_status	STRING	Enum'd result of the filters, indicating if the vehicle id detectable or not.
detected_type_EntityKind	INTEGER	Enumeration value for the true guise - Kind
detected_type_Domain	INTEGER	Enumeration value for the true guise - Domain
detected_type_CountryCode	INTEGER	Enumeration value for the true guise - Country
detected_type_Category	INTEGER	Enumeration value for the true guise - Category
detected_type_Subcategory	INTEGER	Enumeration value for the true guise - SubCategory
detected_type_Specific	INTEGER	Enumeration value for the true guise - Specific
detected_type_Extra	INTEGER	Enumeration value for the true guise - Extra

Obtaining the URBAN RESOLVE data presented some significant challenges for this research effort. Due to the size of the dataset, we were not able to request the entire dataset on a portable media format such as a DVD or CD. Initially we tried to work with a very small subset of the data received on DVD. However, due to database software differences, a significant amount of time was expended to make the data usable with only partial success. Even then, we quickly realized that the subset of data was not sufficient to perform any meaningful analysis. The dataset contained only a four-hour block of time from a single trial. Eventually we were able to gain direct access to the entire dataset via the J9 servers housing the data.

Post analysis data reduction of such large quantities of data presented similar challenges. As with data collection, early data analysis techniques proved problematic as the datasets grew in size. However, the URBAN RESOLVE analysts were able to use another open source tool called PHP (recursive acronym for PHP: Hypertext Protocol) to extract the specific data required to answer the exercise's measures of performance (MOP) (PHP, 2006). Table 3 shows a small portion of the data that was aggregated from the raw dataset. The entire table contains 28,815 rows. Of particular interest to this research are the "initial detection time", "initial identification time", "target type", and "track originating platform." The exercise planners wished to answer three top-level questions:

1) To what extent can situational awareness be developed during JUO?
2) How effectively are sensor data used to detect and correlate targets?
3) What conditions affect Blue capabilities?

Table 3. Track Data table URBAN RESOLVE Phase I Trial 1 (2005)

Target Marking Data	Target Type	Track Number	Track Originating Platform	Track Originating Mode	Track Originating Time (Jakarta timestamp)	Target Originating Time (Jakarta Date)	Target Identifying Platform	Target Identifying Mode	Track Identifying Time (Jakarta timestamp)	Target Identifying Time (Jakarta Date)
2R62	SOLDIER	9	UGSprep	ACOUSTIC	1521025336	Mar 14 2018 06:02:15	UGSprep	ACOUSTIC	1521025336	Mar 14 2018 06:02:15
DD14	T-90 DECOY	9	UAV1A	SPOT_EOIR	1521025456	Mar 14 2018 06:04:16				
44B12	SA-15 TEL	9	UAV4A	LADAR	1521025520	Mar 14 2018 06:05:20				
DD9	T-90 DECOY	9	UAV1A	SPOT_EOIR	1521025678	Mar 14 2018 06:07:57				
27F42	ZIL-157 CARGO TRUCK	9	UAV1A	SPOT_EOIR	1521025697	Mar 14 2018 06:08:17	UAV1A	SPOT_EOIR	1521025697	Mar 14 2018 06:08:17
26C24	BMP-3	9	UAV1A	SPOT_EOIR	1521025697	Mar 14 2018 06:08:17				
27F32	ZIL-157 CARGO TRUCK	9	UAV1A	SPOT_EOIR	1521025701	Mar 14 2018 06:08:20	UAV1A	SPOT_EOIR	1521025701	Mar 14 2018 06:08:20
27F31	BTR-80	9	UAV1A	SPOT_EOIR	1521025701	Mar 14 2018 06:08:20	UAV1A	SPOT_EOIR	1521025701	Mar 14 2018 06:08:20
26C23	BMP-3	9	UAV1A	SPOT_EOIR	1521025701	Mar 14 2018 06:08:20	UAV2A	FOPEN_STRIP _SAR	1521025709	Mar 14 2018 06:08:28
44B11	SA-15 TEL	9	UAV4A	SPOT_EOIR	1521025719	Mar 14 2018 06:08:38	OAV7	MAGNETOME TER	1521033271	Mar 14 2018 08:14:31
44B22	AAA 2S6SP	9	UAV4A	SPOT_EOIR	1521025749	Mar 14 2018 06:09:08	UAV4A	LADAR	1521025750	Mar 14 2018 06:09:09
	SOLDIER	9	UAV4B	TRACKER_EO IR	1521025804	Mar 14 2018 06:10:04	AGS_2	SOF	1521029190	Mar 14 2018 07:06:30
22C11	SOLDIER	9	UAV4A	LADAR	1521025828	Mar 14 2018 06:10:28	UAV1A	SPOT_EOIR	1521025947	Mar 14 2018 06:12:26

This research most directly relates to question three. Each question had a set of MOPs associated with it that are meant to help answer these top-level questions. Similarly, each MOP had approximately twelve measures that were used to evaluate the MOP. Table 4 provides an example of the types of MOPs and measures used in URBAN RESOLVE. Appendix A contains the entire set of MOPs and measures.

Table 4. Example of URBAN RESOLVE MOP and Associated Measures

Q1. To what extent can SA/SU be developed in JUO	
M1.2 Number of Critical Weapon Nodes Identified	
a	Terminal points of Red vehicle paths (see M1.1)
b	Terminal points of Red DI paths (see M1.1)
c	Acquisitions of Red weapon systems (characteristics)
d	Acquisitions of Red weapon systems (location)
e	Acquisitions of Red WMD systems (characteristics)
f	Acquisitions of Red WMD systems (location)

Data Analysis

The analysis performed in this research will focus on two areas: the time to identify (TTI) a target once it has been detected and the rate at which identifications are generated versus time. Each area will be evaluated for patterns or trends between trials, target groups, and detecting sensor type. As mentioned previously the level of effort and resources required to perform a given URBAN RESOLVE event meant that only a single replication was performed for each exercise design trial. Analysis of single replication data presents several difficulties for an analyst. The assumption that the trials are independent or identical cannot be made because exercise participants remained the same for all trials. Ordinarily this may not present a problem, however a definite learning curve was observed in relation to the proficiency of the players. As the exercise progressed, the Blue and Red force operators became more efficient at using the simulation hardware as well as more adept at playing the game. The result was the exclusion of Trial 1 from the original analysis and the loss of the intended "base case." In addition to the unintentional "learning" that was observed, exercise participants on both sides intentionally varied their tactics. Specifically the Blue force was responsible for positioning their available ISR assets before the start of each trial. The Red force was also encouraged to vary their tactics to keep the element of surprise (Burke, 2005:66). Assuming that the distributions of the TTIs for each design case are the same may or may not be reasonable. However, given the similar process that generated them, we assume they are close enough for our purposes. The distributions are not normal and the central limit theorem cannot be used because we lack identical and independent replications for each design trial (Wackerly, 2002:346-348). The distribution variances cannot be assumed the same either.

Although many assumptions about the data cannot be made, nonparametric statistics may still be used to perform statistical analysis (Wackerly, 2002:708-709). Many nonparametric statistics only require that the data be continuous and random (Neter, 1988:481). Unfortunately, in order to perform any form of hypothesis testing still requires independence. A nonparametric confidence interval for the population median can be determined for a large-sample (n >15) single-population using the following method; all data in this analysis contained at least 15 data-points. For a desired 1 - α confidence coefficient for confidence interval $L_r \leq \eta \leq U_r$ such that L_r and U_r are the r^{th}

smallest and largest samples respectively. The variable r is the largest integer that does not exceed the value of equation (1) (Neter, 1988:485).

$$r = 0.5[n + 1 - z(1 - \alpha/2)\sqrt{n}] \quad (1)$$

A large majority of the TTI values are zero because many target identifications are generated by the same sensor that initially detected them. Therefore, it is more appropriate to use the median TTI rather than the mean TTI. The median is the middle of a distribution such that half of all values are above and below it. This makes the median much less susceptible to extreme values than the mean and thus more appropriate for this study.

Summary

This chapter introduced the general experimental architecture and design of URBAN RESOLVE Phase I and pointed out the limitations of an experimental design where more than a single parameter is varied in each trial. Next, it discussed data collection, data reduction, and the difficulties of working with such a large and expanding dataset. Next, this chapter discussed the limitations of working with single-replication datasets that preclude typical parametric statistical methods of analysis. Finally, this chapter discussed a nonparametric method to generate confidence intervals for the median value of that data.

IV. Analysis and Results

Chapter Overview

This chapter details the data analysis performed on the data from URBAN RESOLVE Phase I for this research. Where applicable the analysis involves not only the complete dataset for a given trial, but also decomposition by target-type and the track-originating sensor.

Data Analysis

URBAN RESOLVE Phase I consisted of seven different trials of which six datasets were obtained (Trial 3b was missing). Within each trial folder there was a file containing the complete list of Red Force tracks generated during a run. Each record included the platform, sensor, and time for track detection and, when available, track identification. Track identification data was not available if the track was not identified. This analysis focuses its efforts only on tracks that were identified. The data was manipulated using Microsoft Excel to sort the tracks by identifying time and the TTI was calculated from the difference between the track identifying and originating times. The tracks were sorted again based on TTI and the process was repeated for the remaining trial datasets.

Initially we considered the mean TTI for all tracks. However, the data included a significant number of zero data points which skewed the data (i.e. eighty-nine percent of all tracks in Trial 4b possessed a TTI of zero). A TTI = 0 meant the track was identified immediately by the detecting sensor and is termed an "Instant-ID." In an effort to minimize the effects of these extreme data points, the median TTI was used. Use of the median statistic helps reduce the effect of extreme values. The median is the middle data point such that there are an equal number of data points above and below the median value. However, once the zeros were removed the median TTIs all dropped to 0.0 minutes (Table 5).

Table 5. All Target Types, All IDs

	Trial	Total Detections	Total IDs	Median TTI	Mean TTI	Max TTI	Instant-ID
All Targets	1	28517	10236	0.0	5.9	8398.0	54%
	2a	13847	3352	0.0	5.0	4997.0	63%
	2b	7902	3130	0.0	2.2	4140.0	66%
	3a	8159	3501	0.0	12.9	1425.0	56%
	4a	13385	3888	0.0	2.4	5595.0	84%
	4b	11098	4369	0.0	2.1	5394.0	89%

As a next step in the analysis, the tracks were broken down by target in the hope that some information related to the TTI for different targets may be found within and between the trials. For the purpose of this analysis, and to remain consistent with previous analysis, target types were grouped into eight target groups as shown in Table 6. The target groups categorize the targets such that similar or related targets can be viewed together.

Table 6. Target Groups

Target Group	Target Types	
Artillery	120mm Mortar 105mm Howitzer	
Air Defense	AAA AD Command Vehicle Quad SA18 SA-11	SA-15 SA-15 Decoy ZU-23 Snow Drift Radar
Mechanized	BMP-3 T-90 T-90 Decoy	
TEL, WMD, MTT	BTR-80 MAZ6430 Truck SS26 Command Vehicle	SS26 TEL SS26 TEL Decoy SS26 TEL Reload Vehicle
Leaders	Leaders	
Armed Civilians	Armed Civilians	
Soldiers	Soldiers	
Others	Civilian UNIMOG Truck Military UNIMOG Truck Large Truck Medium Truck URAL Truck	Small Car Motorcyclist SUV SUV Command Vehicle Technical ZIL-157 Cargo Truck

Now that the data was separated by target group, two target groups did possess median TTIs greater than zero. These target groups were the Armed Civilians (Table 7) and Mechanized target groups (Table 8). Within these two target groups only Trials 1, 2b, and Trial 3a, possess non-zero median TTIs. The data for the other target groups may be found in Appendix B.

Table 7. Armed Civilians, All IDs

	Trial	Total Detections	Total IDs	L_r	Median TTI	U_r	Max TTI	Instant-ID
Armed Civilians	1	1729	197	**9.0**	**12.8**	15.7	317.5	21%
	2a	1563	215	**2.7**	**3.4**	4.0	95.2	50%
	2b	414	42	0.0	0.0	2.9	157.9	57%
	3a	3465	702	0.0	0.0	0.2	653.8	52%
	4a	4959	609	0.0	0.0	0.0	171.8	75%
	4b	3689	624	0.0	0.0	0.0	259.9	86%

Table 8. Mechanized Targets, All IDs

	Trial	Total Detections	Total IDs	L_r	Median TTI	U_r	Max TTI	Instant-ID
Mechanized	1	3148	1802	0.0	0.0	0.0	333.8	69%
	2a	3618	462	0.0	0.0	0.0	1081.6	73%
	2b	490	192	0.0	0.0	1.8	149.8	55%
	3a	279	141	**1.4**	**3.9**	7.7	303.9	35%
	4a	518	256	0.0	0.0	0.0	249.6	77%
	4b	371	200	0.0	0.0	0.5	303.6	58%

Although there are three instances, where the median TTI was greater than zero, no confidence level can be associated with those estimates. Using the single-sample confidence interval discussed in Chapter 3, 95% confidence intervals for the median TTI were calculated for the Mechanized and Armed Civilian target groups. The results are shown in Table 7 and Table 8. The column labeled 'r" shows the values calculated using equation (1) while the columns labeled L_r and U_r show the lower and upper bounds of the median TTI at the 95% confidence level. Here we see that the only trial with a lower bound not equal to zero is Trial 3a. We can conclude with 95% confidence that the median TTI for Trial 3a is non-zero. However, a comparison with the other trials is not truly possible because of the lack of independence. Not surprisingly, Trial 3a possessed the fewest identifications with TTI = 0 as evidenced by the 35% Instant-IDs. Trial 3a is also the trial with the fewest total IDs.

As discussed earlier, the experimental design allowed variation of multiple parameters between each trial. As such, it is difficult to make any conclusions about the cause of the non-zero median TTI for Trial 3a relative to the other trials. It is tempting to look at Trial 3a's reduced target signature parameter and conclude that was the cause for the non-zero TTI and even the lower number of Total IDs. However, Trial 4b had both a reduced signature parameter and a reduced sensor inventory parameter, yet still possessed a median TTI lower bound of 0.0 minutes. Similarly, comparisons between Trial 3a and 4a are tempting but the absence of Tags makes it difficult, coupled with Trial 4a's 0.0 minutes median TTI upper bound.

Next, we focused on data points where TTI was greater than zero. These tracks required an additional sensor detection before the target could be identified with confidence. The need for this "second-look" was the result of conditions within the synthetic environment that prevented the sensor from identifying the target with a high degree of confidence. Another cause for second-look identifications were sensors specifically indented to cue another sensor without producing a track on the operator's Shared Tactical Picture display. Analysis of tracks with TTI > 0 was performed on the Armed Civilians and Mechanized target groups. The resulting data can be found in Table 9 and Table 10 respectively.

Table 9. Armed Civilians, TTI > 0

	Trial	Total IDs	Min TTI	L_r	Median TTI	U_r	Max TTI
Armed Civilians	1	155	0.1	14.8	17.4	22.7	317.5
	2a	107	0.1	2.1	2.3	2.9	95.2
	2b	18	2.1	4.0	11.7	21.7	157.9
	3a	339	0.1	6.2	8.6	13.6	653.8
	4a	150	0.5	3.4	3.9	5.1	171.8
	4b	89	0.1	1.7	2.6	4.4	259.9

Table 10. Mechanized Targets, TTI > 0

	Trial	Total IDs	Min TTI	L_r	Median TTI	U_r	Max TTI
Mechanized	1	562	0.1	12.1	14.1	15.5	333.8
	2a	124	0.5	8.5	16.7	31.0	1081.6
	2b	87	0.7	9.2	11.7	14.9	149.8
	3a	92	0.1	8.0	10.9	15.2	303.9
	4a	62	1.6	17.6	24.6	41.2	249.6
	4b	88	0.3	10.8	15.4	19.8	303.6

Figure 4 shows the median TTI along with the 95% upper and lower confidence intervals for the Armed Civilian target group. As Figure 4 shows, the only trial that does not overlap with the majority of the others is Trial 1. Given what we know about the learning curve experiences in the exercise this comes as no surprise. Although Trial 2a overlaps with Trials 2b, 4a, and 4b, it does have the tightest confidence interval. This is an interesting result as it is also only the second trial that occurred where there may have still be some learning occurring. Compared with the other trials, 2a is also the only trial with full inventory and signatures but an inactive force. Recall that the inactive force parameter means 70% of the enemy targets begin the simulation already within the AOI. Further analysis would be required to determine any causal effect between enemy forces that are already inside the AOI vs. ones that could be observed traveling into the AOI.

Trial 3a can be seen outside the ranges of trials 2a, 4a, and 4b and may be an area for further study. Trials 4a and 4b do not appear to be significantly different. This result is curious since when you recall that Trial 4a used the full inventory and full signature design variables while Trial 4b used the reduced level for both parameters. The expectation here would be for there to be a noticeable difference in the ability of the Blue force to find and identify targets. The extremely wide range for Trial 2b may be due to the very low count (18) compared to the other trials.

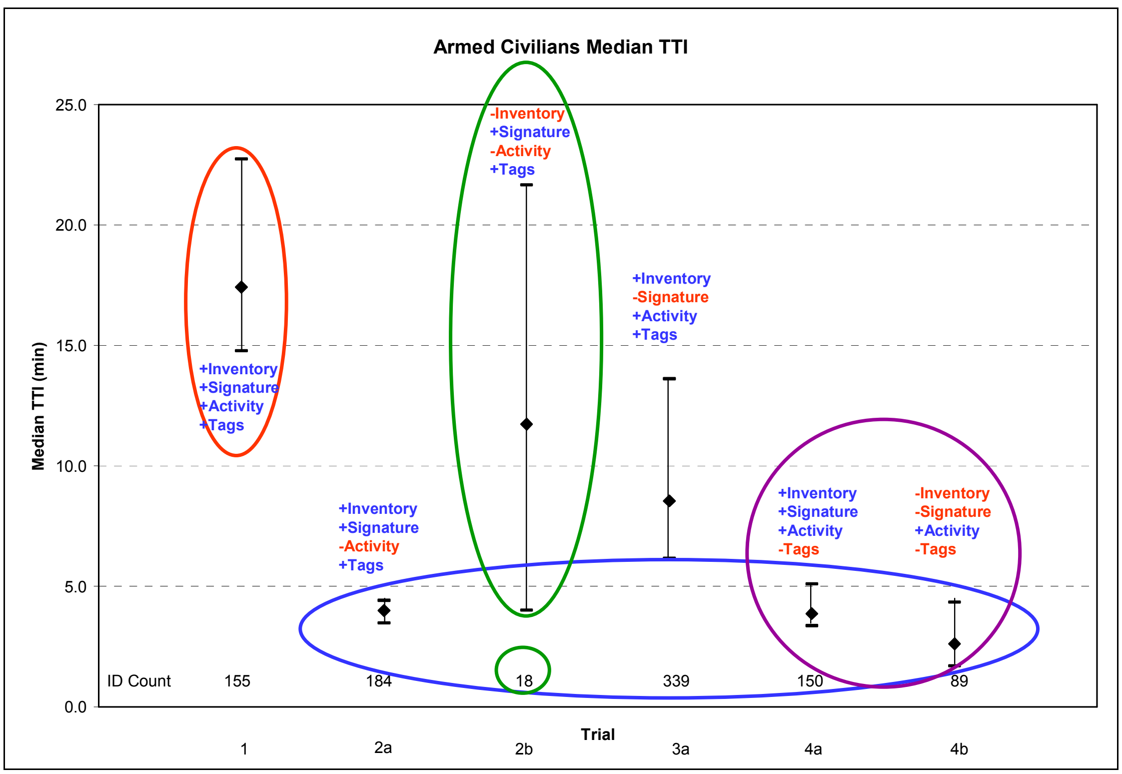

Figure 4. Median TTI and 95% Confidence Interval for Armed Civilian Targets

Figure 5 shows the median TTI along with the 95% upper and lower confidence intervals for the Mechanized target group. The lower bound for Trial 4a is higher than the upper bounds of Trials 1, 2b, and 3a, but not Trials 2a and 4b. Unlike with the Armed Civilians, the confidence intervals for Trials 4a and 4b are close to not overlapping. As mentioned earlier, differences between these two trials are expected. However, the result is even more curious than before because the median TTI for Trial 4a is actually longer than for Trial 4b. The normal expectation would be for this trend to be reversed. Finally comparing the Armed Civilians and the Mechanized targets, we see that the relative size of the confidence intervals is inverted such that trials with the larger intervals in Table 9 possess the relatively smaller intervals in Table 10 and visa versa. Although there is no apparent explanation for the result, it begs the question why.

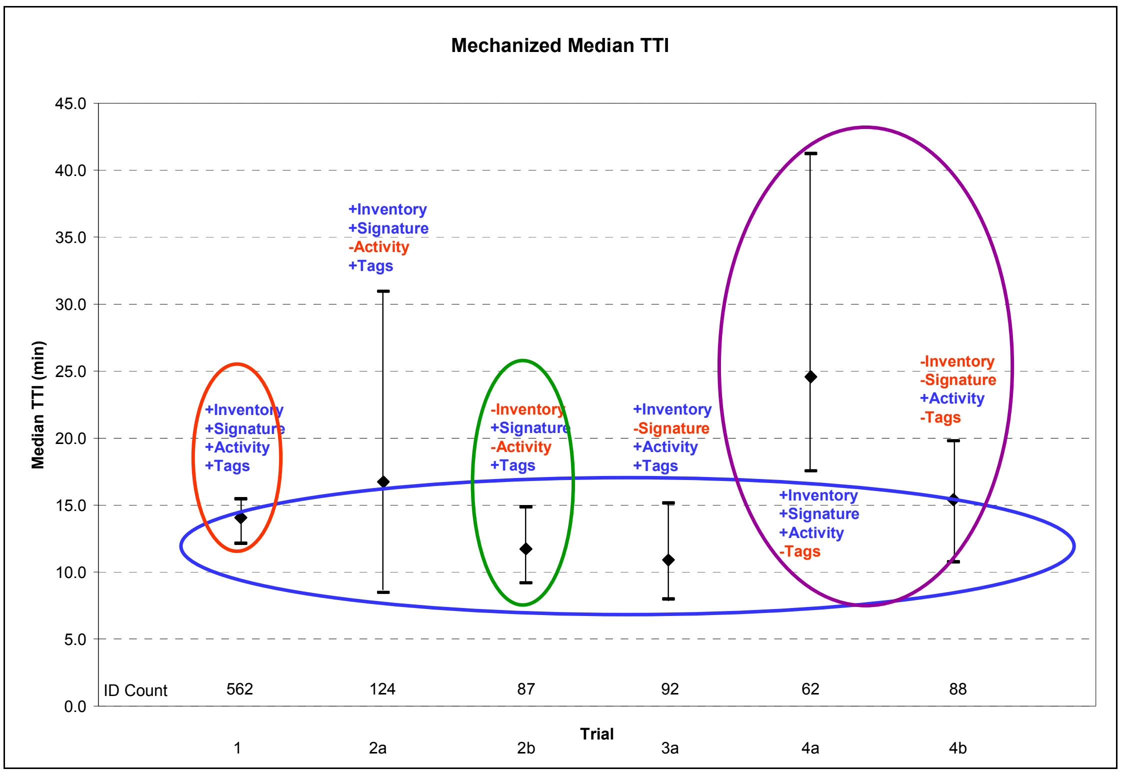

Figure 5. Median TTI and 95% Confidence Interval for Mechanized Targets

Next, we looked at the tracks based on the initial detecting platform (UAV and OAV) and the corresponding TTI. The UGSs were not included because they represented a very small proportion of the total track detections (~2%). Table 11 shows the total number of IDs produced by both platforms, the total number of IDs with TTI > 0, the median TTI for all non-zero TTIs and their 95% confidence intervals. The first item of interest is the All IDs count. The OAVs produced significantly more IDs than the UAVs. This is not a surprising result considering there were approximately five times as many OAVs in each trial as there were UAVs, however the OAV's All IDs counts are not consistently five time larger than the UAVs. When looking only at the IDs where TTI is greater than zero, the OAVs in Trial 1 are the only significant outliers from the rest of the OAV. The fact that Trial 1 has such a tight confidence interval and lower median TTI is notable given the learning that is supposed to have occurred during Trial 1 as well as the large track count which would normally result in a wider spread of values. Further analysis may explain why detections generated by the OAVs in Trial 1 required so little time to identify in comparison to the other trial. Unfortunately, not much else can be said about the data. The UAV TTI confidence intervals all overlap with both each other and their corresponding OAV values.

Table 11. TTI Data for UAVs and OAVs

	UAV						OAV					
	All IDs	Tracks with TTI > 0					All IDs	Tracks with TTI > 0				
Trial	Count	Count	*r*	*Lr*	Median TTI	*Ur*	Count	Count	*r*	*Lr*	Median TTI	*Ur*
1	2715	1002	470	4.4	5.1	5.7	6243	3040	1466	3.5	3.9	4.3
2a	761	76	29	1.4	1.7	2.1	2410	1044	490	7.8	8.0	8.2
2b	39	16	4	1.3	2.2	15.5	2563	651	300	6.0	6.6	7.9
3a	555	24	7	2.3	4.5	16.6	2480	1155	544	4.8	5.7	6.2
4a	838	14	3	0.5	3.2	23.6	2814	520	238	6.6	8.1	9.7
4b	897	50	18	2.3	11.3	16.0	3108	343	153	8.0	9.6	11.2

A final attempt to extract useful information from the data focused on the how fast IDs were generated in each trial for the Armed Civilians and Mechanized Targets; all ISR platforms were included. Two charts were generated for each target group, an accumulated ID count, and a proportion of the total ID count. Figure 6 and Figure 7 show the data for the Armed Civilians and Figure 8 and Figure 9 show the data for the Mechanized targets. Note that in Figure 8 the chart stops at 24 hours in order to better illustrate the differences between the trials. Figure 6 shows a few interesting features. Trial 3a accumulated identified targets significantly faster than all other trials. Again, because of the experimental design it is difficult to determine an exact cause with another trial to compare to with only single parameters being changed. However, it is interesting to note that Trial 3a does have the reduced signature parameter yet still generated more targets, faster than all other trials. Similarly, Trials 1 and 2b showed that significantly fewer tracks were accumulated at a slower rate. Although difficult to pinpoint the cause, Trial 1 makes sense due to learning, and Trial 2b because of the reduced sensor inventory, inactive force, and only 18 hours worth of data. Even if Trial 2b had continued for another 6 hours, the slope of the curve indicates it is unlikely to have caught up to 3a, 4a, or 4b. A very interesting result is the apparent similarity between Trials 4a and 4b. The two parameters that are varied between these trials (inventory and signature) lead to the natural assumption that Trial 4b should accumulate fewer tracks at a slower rate. Further analysis may be warranted to determine why this is occurring.

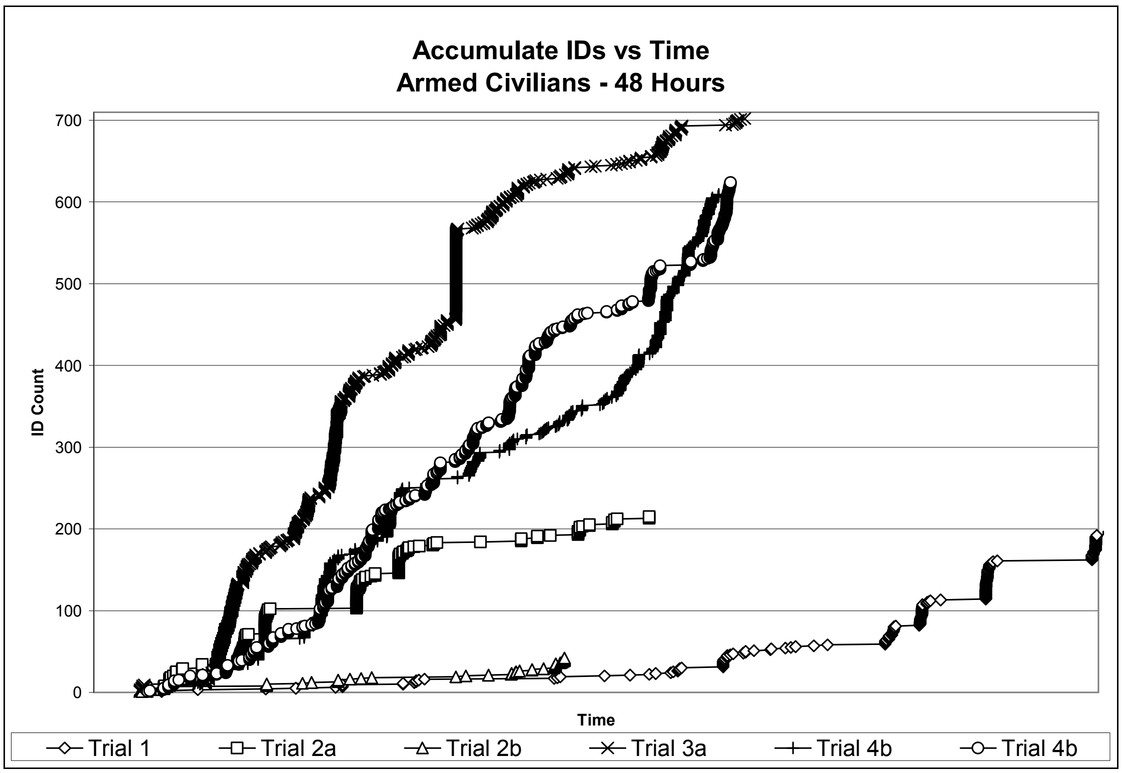

Figure 6. Accumulated IDs vs. Time for Armed Civilians

The proportional accumulation of Armed Civilians shown in Figure 7 shows an interesting trend for Trial 1 where it appears that the IDs accumulate very slowly at first then accelerates at an increasing rate after the first 24-hours. Note that because of the 48-hour run time of Trial 1 it has been displayed in two 24-hour segments. The first segment clearly shows a slower accumulation of identifications with a sudden increase in the 23rd hour. The second segment of Trial 1 is on par with the other trials. This behavior is likely indicative of the learning discussed in the original URBAN RESOLVE analysis. All of the other trials appear to accumulate their IDs at a similar and linear rate. Additional replications would be required before additional insight could be gained concerning the shape of the curves. Trial 2b was removed because of its 18-hour timeframe.

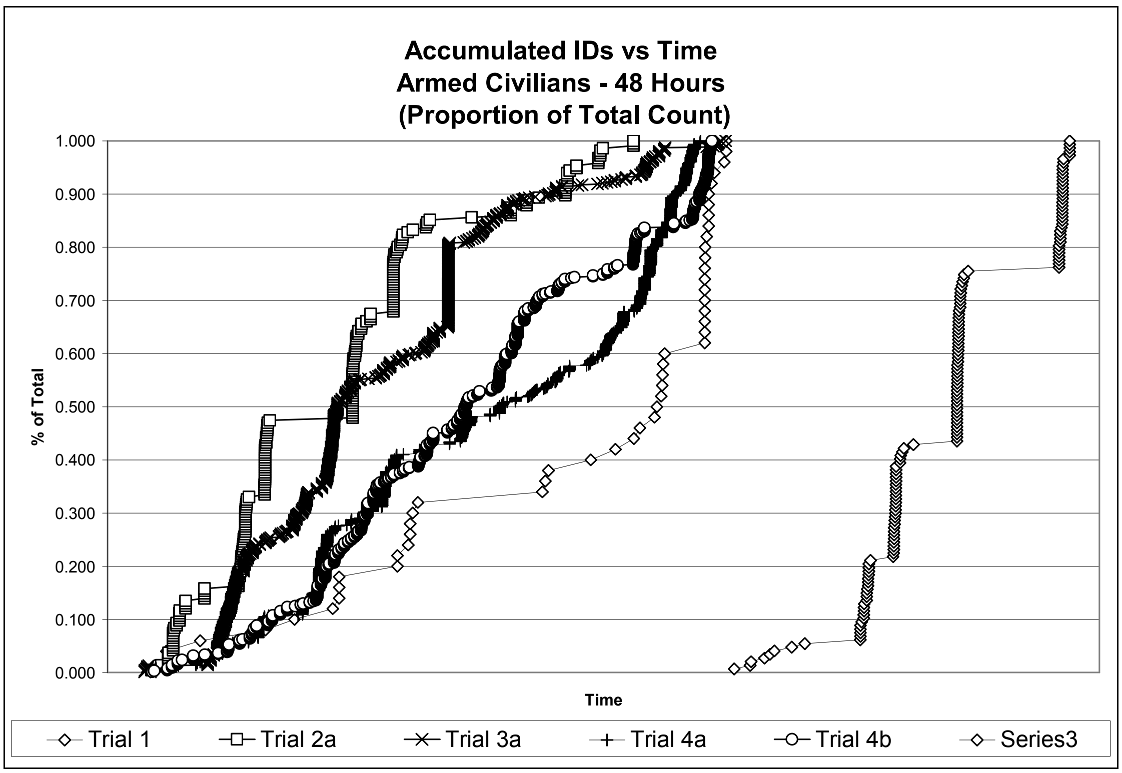

Figure 7. Proportion of Total Accumulated IDs vs. Time for Armed Civilians

Figure 8 shows a rather different story from Figure 6. Here Trial 1 accumulates many more Mechanized target IDs at a much faster rate and Trial 3a accumulates the fewest IDs at the slowest rate. Trials 4a and 4b now show a slight difference in both accumulation total and rate; however, it is only a slight difference especially considering the inventory and signature difference between them and compared to Trials 1 and 2a. Trial 2b managed to accumulate IDs at a comparable rate to Trials 4a and 4b, and the data at least suggests that it would have accumulated a similar number of IDs had it continued for the full 24 hours. Finally, Trial 2b compares more similarly with the other trials and shows a marked difference compared to the Armed Civilians where it accumulated identifications on par with Trial 1 and much slower than the other trials.

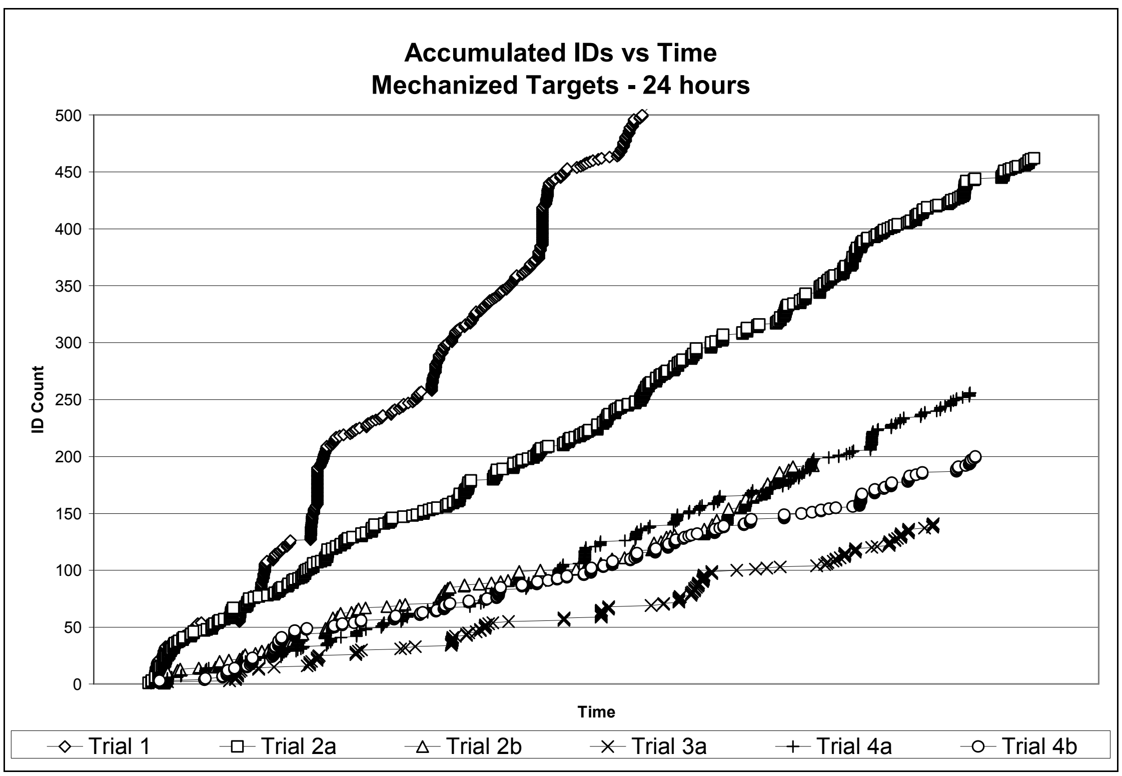

Figure 8. Accumulated IDs vs. Time for Mechanized Targets

Finally, Figure 9 shows the proportional accumulation of Mechanized IDs. Again, the curve for Trial 2b has been removed because of its 18-hour timeframe. As before, Trial 1 has been split into two 24-hour sections. The fist 24 hours shows a slightly slower accumulation compared to the other trials but not nearly to the extent as with the Armed Civilians. The second segment of Trial 1 shows an accumulation that is significantly steeper than the other trials especially compared to the second segment of Trial 1 for the Armed Civilians. Although there is not a significant difference between the trials of the Mechanized IDs, the difference between the two target groups is interesting.

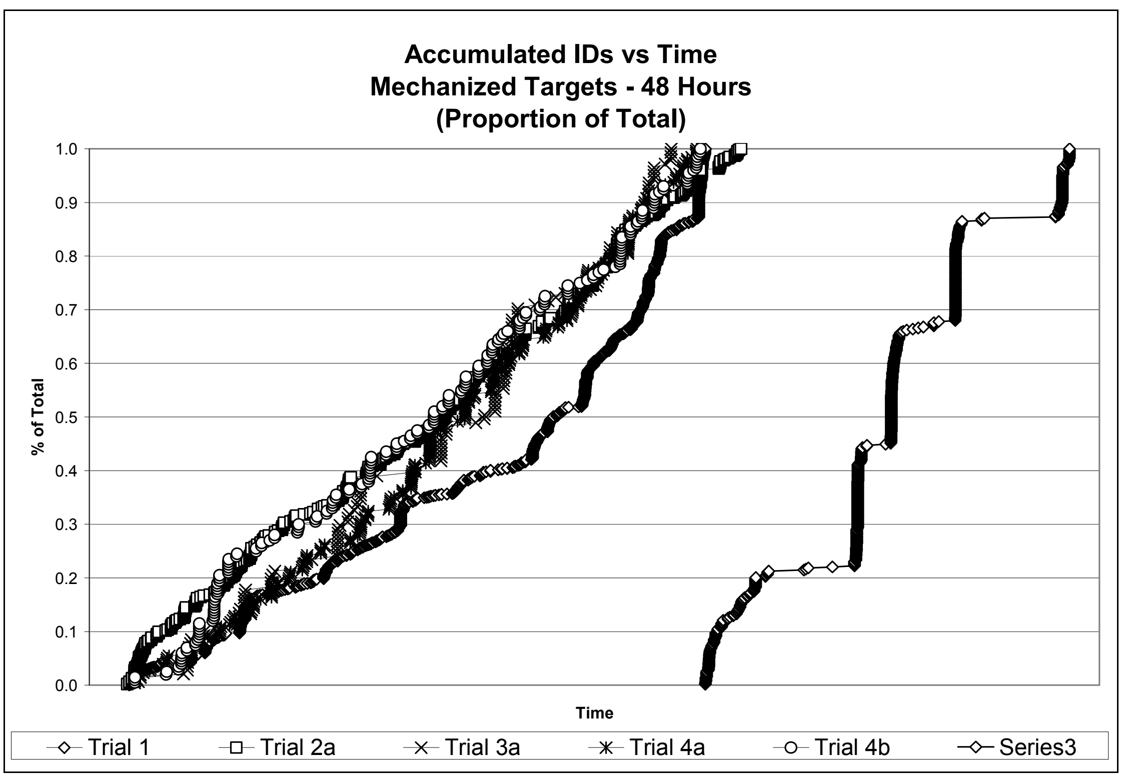

Figure 9. Proportion of Total Accumulated IDs vs. Time for Mechanized Targets

Summary

This chapter detailed various attempts to distill useful information from the vast data set created in the URBAN RESOLVE exercise despite significant limitations due to the experimental design and lack of replications. Non-parametric statistical techniques were used to calculate 95% confidence intervals for the median TTI for all target types and for each target group. Analysis of all Armed Civilian and Mechanized target group IDs showed that Trials 2a and 3a had non-zero TTIs with 95% confidence. Analysis of only the identifications requiring a second-look (TTI > 0) showed some interesting, though inconclusive, trends that run counter to what would be anticipated. This chapter also discussed the analysis of TTI data relative to the initial detecting platform (UAV vs. OAV). Finally, this chapter discussed the analysis of the accumulation rate of identification versus time for the Armed Civilian and Mechanized target groups. Some interesting trends were noted which may indicate possible areas for deeper analysis.

V. Conclusions

Chapter Overview

This chapter will provide a summary discussion of this research effort. First, it will discuss the results of the analysis performed during this research effort. Next will be a brief discussion of the obstacles encountered during the course of this research. Finally, it will suggest areas for further research in this topic area.

Analysis Results

This research identified two notable trends in the URBAN RESOLVE data. First, despite the "learning" that took place during Trial 1, the TTI for all target types was zero minutes for all of the trials. When looking at individual target groups, the Armed Civilians were the only target group with a Trial 1 TTI that stood out as different from the other target groups. When examining only the IDs with TTI > 0, the Armed Civilians in Trial 1 seemed to possess a noticeably longer TTI. This result is to be expected given the "learning" that was supposed to have taken place. However, when examining the TTIs for the Mechanized target group, Trial 1 was reasonably similar compared to the other trials. Finally, analysis of the accumulated IDs versus time showed a similar result where fewer Armed Civilians were identified at a slower pace in Trial 1 compared to the other trials. On the other hand, the exact opposite was true for the Mechanized target group where many more targets were identified at a much faster rate than the other trials.

Second, although it is difficult to make causal comparisons relative to the design parameters and results, Trials 4a and 4b provide the best chance to observe the difference between what can be considered the best case scenario (full inventory / full signature) and worst case scenario (reduced inventory / reduced signature) with no other differences in design. However, what was observed most often was at best a complete lack of differentiation between the two trials, and at worst, results that appeared completely counter intuitive to the expected results. The initial URBAN RESOLVE report noted that Trials 4a and 4b helped demonstrate the importance of Tags when compared to the other trials.

The two trends mentioned above raise questions that bare further study:

- Why are the Armed Civilians noticeably different from the other target groups?
- Why does the Mechanized target group exhibit different behavior from the Armed Civilians?
- Why are the results from Trials 4a and 4b so similar in some cases and counter-intuitive in others?

Obstacles

During the initial phases of this research, the intent was to investigate possible applications of JSAF in simulating the Air and Space Operations Center (AOC) and possible applications related to modeling of the time sensitive targeting (TST) kill-chain. The goal was to generate an appropriate environment and scenario in JSAF and to use that environment to investigate the ability to simulate the Combat Operations TCT cell of an AOC. However, it became apparent that such an effort was too large an undertaking for the time and resources available.

As research progressed, and the existence of JSAF's use by other agencies became known, the hope was to build on their research and possibly modify their scenarios. Attempts were made to acquire some portion of the URBAN RESOLVE scenario in the hope that it could be used to perform simulations locally. However, even that proved impossible. A JSAF scenario cannot be easily broken down into pieces for independent use. The very strengths of JSAF that make it such a powerful tool, its ability to operate in real-time with HITL participants and a large numbers of autonomous entities generated through multiple distributed computing clusters, makes its utility trivial when operated on a single workstation. A project that seemed ambitious at first quickly became impossible as time marched on.

Ultimately, the scope and scale of the URBAN RESOLVE exercise presented a possible foothold for research. The sheer size of the dataset promised to be a treasure trove for analysis, however very size of the dataset made it difficult to obtain. After nearly five weeks of unsuccessful attempts to acquire and convert a four-hour portion of data (8GB), we were finally able to access the entire dataset housed on the J9 servers via the DREN.

Recommendations for Future Research

Several avenues for further research readily present themselves in relation to past and future incarnations of URBAN RESOLVE. Analysis to answer the questions raised in this research may help improve the design of future URBAN RESOLVE events. Additional research using more sophisticated data mining techniques may illuminate additional trends in the data that have not yet been discovered. Another area for future research is the development of pattern recognition tools to cue operators towards possible activity of interest based on track identity, behavior, and proximity to other tracks.

Finally, multiple replications of the trials, using different groups of operators, may provide a deeper analysis and expose unseen trends.

Appendix A. Analysis Questions and Measures of Performance

Q1. To what extent can SA/SU be developed in JUO	
M1.1 Number of Critical Command Nodes Identified	
a	Terminal points of Red vehicle paths
b	Terminal points of Red DI paths
c	Red Vehicle congregation points
d	Red DI congregation points
e	Buildings housing several (> n) Red vehicles
f	Buildings housing many (> n) Red DI
g	Number of RF transmissions from individual bldgs
h	Number of RF transmissions from specific locations
M1.2 Number of Critical Weapon Nodes Identified	
a	Terminal points of Red vehicle paths (see M1.1)
b	Terminal points of Red DI paths (see M1.1)
c	Acquisitions of Red weapon systems (characteristics)
d	Acquisitions of Red weapon systems (location)
e	Acquisitions of Red WMD systems (characteristics)
f	Acquisitions of Red WMD systems (location)
M1.3 Number of Other Critical Nodes (or patterns) Identified	
a	Terminal points of Red vehicle paths (M1.1)
b	Terminal points of Red DI paths (M1.1)
c	Red Vehicle congregation points (M1.1)
d	Red DI congregation points (M1.1)
e	Vehicle relative positions while in transit (signature formations)
f	DI relative positions while in transit (signature formations)
g	Number of features detected
h	Number of features recognized
I	Number of features identified
j	Locations of detected features
k	Locations of recognized features (by category)
l	Locations of identified features (by category)

M1.4 Anticipated Red Activities	
a	Number of tracks of duration > n minutes [n = 5, 10, 15, …]
b	Number of tracks in which targets are correctly identified for > n minutes
c	Number of tracks in which targets are correctly recognized for > n minutes
d	Number of tracks in which targets are correctly classified for > n minutes
e	Number of false targets tracked for > n minutes
f	Number of tracks in which targets are incorrectly classified for > n minutes
g	Number of tracks in which targets are incorrectly recognized for > n minutes
h	Number of tracks in which targets are incorrectly identified for > n minutes
i	Duration of tracks for all categories above
j	Number of features detected through "Change Detection"
k	Number of features recognized through "Change Detection"
l	Number of features identified through "Change Detection"
m	Locations of features detected through "Change Detection"
n	Locations of features recognized through "Change Detection"
o	Locations of features identified through "Change Detection"

Q2. How effectively are sensor data used to detect and correlate targets?	
M2.1. Track Profile and Utility	
a	Number of tracks of duration > n minutes; n = 5, 10, …
b	Track identifiers (trks > n min)
c	Target ids (trks > n min)
d	Major and minor axes of position estimates (trks > n min)
e	True target type (trks > n min)
f	Perceived target type (trks > n min)
g	Sensors contributing to establishing/maintaining the track
h	Platforms contributing to establishing/maintaining the track
I	Sensor-Platform combinations (e.g., MWIR/ NFOV - UAV 3) contributing to establishing/ maintaining the track
M2.2. Time to correlate target acquisitions	
a	Number requiring > n minutes from detection to establishing track; n = 5, 10, …
b	Number requiring > n minutes from detection to classification; n = 5, 10, …
c	Number requiring > n minutes from initial acquisition to recognition; n = 5, 10, …
d	Number requiring > n minutes from initial acquisition to identification; n = 5, 10, …

M2.3 Effectiveness of Each Sensor System (e.g., MWIR/ WFOV)	
a	Population of targets of each type (function of time)
b	Bubble charts of sensor target interactions (number of interactions)
c	Number of each type target detected by each sensor class (unique entities detected)
d	Number of each type target correctly recognized by each sensor class
e	Number of each type target correctly identified by each sensor class
f	Number of each type target incorrectly recognized by each sensor class
g	Number of each type target incorrectly identified by each sensor class
h	"Failed Detections" by Sensor class due to MDV
I	"Failed Detections" by Sensor class due to [each of] bldg/foliage/vehicle obscuration
j	"Failed Detections" per Sensor by class due to MDV
k	"Failed Detections" per Sensor by class due to [each of] bldg/foliage/vehicle obscuration
l	Sensor class providing initial acquisition of each target (may be emission)
m	Sensor class providing initial correct recognition (possibly none)
n	Sensor class providing initial correct identification (possibly none)
o	Sensor classes (PLURAL) responsible for establishing track
M2.4 Effectiveness of Each Sensor-Platform Class (e.g., MWIR/WFOV - UAV3)	
a	Population of targets of each type (function of time) [see M.2.3]
b	Number of each type target detected by each sensor-platform class
c	Number of each type target correctly recognized by each sensor-platform class
d	Number of each type target correctly identified by each sensor-platform class
e	Number of each type target incorrectly recognized by each sensor-platform class
f	Number of each type target incorrectly identified by each sensor-platform class
g	"Failed Detections" by Sensor-Platform class due to MDV
h	"Failed Detections" by Sensor-Platform class due to [each of] bldg/foliage/vehicle obscuration
i	"Failed Detections" per Sensor-Platform by class due to MDV
j	"Failed Detections" per Sensor-Platform by class due to [each of] bldg/foliage obscuration
k	Sensor-Platform class providing initial acquisition of each target
l	Sensor-Platform class providing initial recognition
m	Sensor-Platform class providing initial identification
n	Sensor-Platform classes responsible for establishing track
o	Sensor-Platform classes responsible for update that "correctly identifies" track

M2.5 Effectiveness of Each Platform Class (e.g., UAV3)	
a	Population of targets of each type (function of time) [see M.2.3]
b	Number of each type target detected by each platform class (unique entities)
c	Number of each type target correctly recognized by each platform class
d	Number of each type target correctly identified by each platform class
e	Number of each type target incorrectly recognized by each platform class
f	Number of each type target incorrectly identified by each platform class
g	"Failed Detections" by Platform class due to MDV
h	"Failed Detections" by Platform class due to [each of] bldg/foliage/vehicle obscuration
i	"Failed Detections" per Platform by class due to MDV
j	"Failed Detections" per Platform by class due to [each of] bldg/foliage/vehicle obscuration
k	Platform class providing initial acquisition of each target
l	Platform class providing initial recognition
m	Platform class providing initial identification
n	Platform classes responsible for establishing track
M2.6 Sensor platform tasking and retasking responsiveness	
a	Time of each sensor request, by type of sensor and platform
b	Type of request (automated retasking, operator decisions, etc.)
c	Time request is received by controlling agent (sensor type and platform)
d	Time task or retask begins (sensor type and platform)
e	Time of arrival of retasked platform in target area
f	Length of retasking chain [how many platforms are retasked serially, parallel?]
g	Outcome [failed to find target][found intended target][found something]
h	Time [if successful] sensor acquires intended target (sensor type and platform)
M2.7 Timing and events in target prosecution chain	
a	Time of initial detection
b	Type of sensor performing initial detection (see M2.3)
c	Type of platform performing initial detection (see M2.3)
d	Time higher level sensor is tasked to query detected target
e	Type of sensor tasked for higher level acquisition (See M2.3)
f	Type of platform tasked for higher level acquisition (see M2.3)
g	Time of higher level acquisition(s)
h	Type of sensor performing higher level acquisition (see M2.3)
i	Type of platform performing higher level acquisition (see M2.3)
j	Time of declaration "target of interest"
k	Time of declaration "target is recommended"
l	Operator override of sensor-provided track identity (time and imposed type)

Q 3. What conditions affect Blue capabilities?	
M3.1 Impact of Terrain and Buildings on sensor operations	
a	RSS Event Codes for masking (reasons for missed detections)
b	Camouflage State of missed targets in sensor window
c	Number of false alarms and mis-acquisitions in "n" minute windows
d	Targets never detected [type, number, location]
e	Locations of detected targets [downtown, city parks, highway, shanty town, etc]
f	Location where tracks are established [downtown, city parks, highway, shanty town, etc]
g	Location where tracks are lost [downtown, city parks, highway, shanty town, etc]
h	Time-position history of gaps in tracks
M3.2 Temporal effects on sensor operations	
a	RSS Event Codes for masking (reasons for missed detections) by time
b	Camouflage State of missed targets in sensor window by time (same as above?)
c	Number of false alarms and mis-acquisitions in "n-minute" windows
d	Time tracks are established [morning rush hour, midday, evening rush, nighttime, etc]
e	Time tracks are lost [morning rush hour, midday, evening rush, nighttime, etc]
f	Time history of gaps in tracks
M3.3 Impact of Red Counter Measures on sensor operations	
a	RSS Event Codes for masking (reasons for missed detections)
b	Camouflage State of missed targets in sensor window
c	Sensors neutralized/compromised by deliberate Red action
d	Platforms destroyed by Red munitions
M3.4 Actions most favorable to Red	
a	Red formations when acquired [small group, large group, individual vehicle/DI]
b	Red formations when not acquired [small group, large group, individual vehicle/DI]
c	Red Activity when acquired [on road movement, WMD set up, static, etc]
d	Red Activity when not acquired [on road movement, WMD set up, static, etc]
e	Location where acquired [M3.1]
f	Location where not acquired [M3.1]{where Red is unlikely to be detected}
g	Time when acquired [M3.2]
h	Time when not acquired [M3.2]{when Red is unlikely to be detected}
M3.5 Communications	
a	Histogram of lengths of messages sent (bytes), aggregated and by transmitter type
b	Histogram of lengths of messages received (bytes)
c	Number of messages sent as a function of time, aggregated and by transmitter type
d	Number of messages received as a function of time
e	Number of messages transmitted but not received due to no LOS
f	Number of messages transmitted but not received due to low power (SLMM)
g	Number of messages transmitted but not received due to reasons other than LOS or PWR
h	Histogram of number of lost messages by reason for loss.

Appendix B. Additional Analysis Results

Soldiers, All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
Soldiers	01	13309	5082	227.0	6.3	14.9	0.9	2471	0.8	1.1	30%
	02a	2442	1577	34.1	3.9	5.2	0.7	749	0.5	0.9	44%
	02b	2460	1933	71.6	2.2	4.9	0.0	923	0.0	0.2	51%
	03a	2722	1905	575.0	5.3	20.1	0.6	910	0.0	0.9	48%
	04a	1773	1270	77.9	2.9	7.3	0.0	600	0.0	0.0	75%
	04b	1407	1181	95.2	2.0	7.2	0.0	557	0.0	0.0	82%

Other Target Types All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
Others	01	8398	1888	265.5	1.3	9.3	0.0	901	0.0	0.0	91%
	02a	4997	839	84.7	0.2	3.2	0.0	391	0.0	0.0	98%
	02b	4140	811	2.5	0.0	0.2	0.0	377	0.0	0.0	98%
	03a	1425	587	451.9	1.7	20.9	0.0	270	0.0	0.0	88%
	04a	5595	1572	27.7	0.2	1.1	0.0	747	0.0	0.0	95%
	04b	5394	2195	323.4	0.4	7.3	0.0	1051	0.0	0.0	96%

Artillery Target Types, All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
Artillery	01	367	318	25.1	0.4	2.3	0.0	141	0.0	0.0	93%
	02a	132	49	0.0	0.0	0.0	0.0	18	0.0	0.0	100%
	02b	62	62	0.0	0.0	0.0	0.0	23	0.0	0.0	100%
	03a	66	52	75.6	4.4	14.2	0.0	19	0.0	0.0	69%
	04a	111	87	0.0	0.6	0.0	0.0	34	0.0	0.0	100%
	04b	83	80	28.4	0.6	3.4	0.6	31	0.0	0.0	91%

Air Defense Target types, All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
Air Defense	01	845	453	240.5	10.2	25.7	0.0	206	0.0	0.0	66%
	02a	206	67	690.9	19.0	86.6	0.0	25	0.0	0.0	81%
	02b	244	48	59.5	4.3	12.6	0.0	17	0.0	0.0	83%
	03a	161	91	484.1	21.1	70.8	0.0	36	0.0	0.0	67%
	04a	370	52	44.7	6.1	11.6	0.0	19	0.0	0.0	71%
	04b	112	65	71.7	7.4	12.3	0.0	25	0.0	6.9	55%

TEL, WMD, MTT, All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
TEL, WMD, MTT	01	637	495	86.0	2.1	8.4	0.0	226	0.0	0.0	88%
	02a	864	143	2.6	2.9	12.9	0.0	60	0.0	0.0	96%
	02b	86	43	54.0	3.0	9.8	0.0	15	0.0	0.0	88%
	03a	31	24	626.8	80.5	176.1	0.0	7	0.0	28.6	63%
	04a	41	34	25.2	0.9	4.4	0.0	11	0.0	0.0	94%
	04b	35	25	10.5	0.7	2.2	0.0	8	0.0	0.0	88%

Leaders, All IDs

	Trial	Total Detections	Total IDs	Max ID Time	Mean	STD	Median	r	Lr	Ur	Instant-ID
Leaders	01	84	2	0.0	0.0	0.0	0.0	0	---	---	100%
	02a	25	1	0.0	0.0	0.0	0.0	0	---	---	100%
	02b	6	0	0.0	---	---	---	0	---	---	
	03a	10	0	0.0	---	---	---	0	---	---	
	04a	18	9	0.8	0.2	0.3	0.0	2	0.0	0.6	56%
	04b	7	0	0.0	---	---	---	0	---	---	

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14. ABSTRACT

The United States military is performing operations in urban environments with increasing frequency. Current Department of Defense doctrine is poorly suited to train and equip today's warriors with the tools and experience necessary to fight and win in modern sprawling cities. In order to "close the gap," the U.S. Joint Forces Command's Joint Experimentation Directorate led an effort to run a massively distributed simulation of a synthetic urban environment utilizing human-in-the-loop operators called URBAN RESOLVE. The synthetic environment simulated the city of Jakarta with over 1,000,000 buildings and structures and over 120,000 civilian entities. A Red force retreated into the city while a Blue force attempted to determine the enemy's Order of Battle. The exercise generated over 3.7 terabytes of data in seven distinct trials. This research evaluated the time required to identify targets after detection and the accumulation of identifications over time, and searched for trends between the seven design trials and between target groups. Two trends emerged from this research. First, there was a notable difference in the time required to identify a target once it has been detected based on its target group. Second, two design trials that are expected to demonstrate show counter-intuitive results.

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